Uncertainty and Risk Models for Decision-Making Processes

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ABSTRACT

In mine design and mine planning activities it is sometimes assumed that the block model provided by geologists or ore reserve estimators have no associated errors or uncertainties. This is usually the case simply because mine planners do not have a practical and useful way of quantifying this uncertainty on a block by block basis. The possible variations in ore resources and reserves are typically handled by applying a very simplistic sensitivity analysis to the, for example, pit optimization process. This can be done by adding or subtracting an arbitrary amount of contained metal to the block model that represents the ore resources, and observing the difference in resulting minable reserves and mine plans, and cash flows derived from them.

This sensitivity analysis has several shortcomings. The manipulation of contained metal is done on a global basis, without regard for the geology and the local variations in grade. In addition, the arbitrary amount of metal added or subtracted does not provide a realistic uncertainty model that would take into account estimation errors, such as those caused by imperfect sampling, imperfect geologic modeling, imperfect grade modeling, and intrinsic mineralization variability. Therefore, the sensitivity analysis generally done has no geologic support, and therefore there is no rational basis to believe in it.

Geostatistical conditional simulations have been proposed in the past as models that fully describe the uncertainties involved in predicting ore resources. These models have theoretical and practical characteristics that allow them to provide the best alternative yet for risk analysis in mine planning. This paper will discuss some of these theoretical advantages, and will illustrate the practical aspects of using conditional simulations to support mine design and planning and management's decision-making. As illustration, a case study developed for a large operating porphyry copper mine will be presented here. In this case the conditional simulations were used to assess the risks in achieving mine extraction targets for a significant expansion plan proposed to almost double current copper production.

INTRODUCTION

The risks associated with the ore reserves used to plan a mine usually are either ignored or mishandled. Most mines operating in the mining industry could benefit from a more honest recognition of the existence of reserve-related risks and the use of models that quantify that risk. Reserve reporting, pit or mine designs, projected cash flows, project financing, operating plans, and ultimately shareholder value depend on an accurate assessment of the basic asset, the resource estimate itself.

Figure 1 (reproduced from Baker and Giacomo, 1998), shows a group of well-known new mines and projects in Australasia. The impact of economic losses through either under- or over-stating the reserve grade (lost investment capital or opportunity costs) is staggering, note the x-axis scale. The advantage of quantifying upside and downside potential for all these projects is quite obvious.

Geostatistical conditional simulations are becoming increasingly popular in recent years, mainly due to availability of virtually-free software and cheap hardware. In addition, accumulated experience in performing industrial-scale simulations is now significant, and there is a better understanding of the usefulness of conditional simulations, as well as the potential pitfalls. Some of the more important aspects of conditional simulations, theory and practice, have been described elsewhere, see for example Goovaerts (1997), Rossi and Van Brunt (1997), and Rossi (1998). Multiple simulations (models of the deposit) are required to characterize uncertainty. This is because each simulation is interpreted as a possible, equi-probable image of the deposit, meaning it has the same likelihood of being reality as any other simulation. Multiple images (obtained using a Monte-Carlo approach) can thus describe the expected range of variability for any particular block. The resulting range of variability, and thus the set of conditional simulations, is termed a “model of uncertainty”, since it quantifies the possible minimum and maximum values for any and all blocks in the model. In this author’s experience between 10 and

20 conditional simulations are sufficient to describe adequately this range of variability. This is, of course, a function of the variability of the grade distribution being analyzed (gold deposits exhibit more variability than porphyry copper, for example), and the amount of drill hole data available (conditioning). In any case, the simulations will provide a model of uncertainty that can be used to quantify risk.

It is important to note that the risk that mine managers are usually interested in is the risk associated with production predictions. These are a consequence of a mine plan, whose level of detail depends on which stage the project or operating mine is at. The cumulative processes that occur between producing a model of reserves and resources and a detailed mine plan, schedule, and predicted cash flow will be termed here a "Transfer Function" (Matheron, 1975, Rossi and Alvarado,1998).

The paper will describe the methodology used to quantify risk for an operating mine, where the central issue was to incorporate risk analysis into the feasibility study for a significant production expansion. Thus the transfer function includes the pit optimization and detailed mine planning and scheduling activities.

DESCRIPTION OF THE CASE STUDY

The subject of this case study is a major porphyry copper mine in northern Chile, which entered production only recently. An increase of the reserves which were the base for the original mine design was soon believed to be sufficient for supporting a production rate increase, and an overall production expansion by about 60%. The mine produces copper using SX-EW technology from an overall oxide mineralization reserve base of just under 900 million tons of 0.54% Cu. In addition, there are also significant secondary enriched and primary Cu mineralization not considered in this study.

Given the significant amount of capital investment required to achieve this expanded production, management decided that an evaluation of risk on the reserves and its impact on the extraction schedule and overall mine plan was necessary. Therefore, a conditional simulation study was commissioned, with the main objective being quantifying the upside and downside potential of the existing mine plan for the expanded production.

Uncertainty (risk) stems from several sources, the most important being:

1. The quality of original, conditioning information; this refers specifically to the quality of drilling, sampling, and assaying.
2. The quality of the geologic model, and to what extent the interpreted geologic controls are relevant and have been correctly interpreted. This is key to a reasonable prediction of tonnage above cutoff, since in many cases the geologic model is used to constrain the grade interpolation, as is the case at this copper mine.
3. The process of grade interpolation itself, which requires a correct amount of smoothing in order to predict the grade and tons of material available at the time of mining. The main

concern is the volume-variance effect, i.e., accurately predicting recoverable reserves.

The study concentrated on characterizing the third major component described above (grade interpolation and recoverable reserves); naturally, the quality of the final grade estimate is impacted by the quality of the initial drill hole information, and so indirectly, it included characterization of the first item mentioned. However, it is possible to develop more explicit studies to decompose and analyze separately the impact of poor quality drill hole data. This was not done in this case study.
Similarly, it is possible to analyze the contribution to risk stemming from the interpretation and interpolation of the geologic controls on mineralization (geologic models). In this case, the interpreted geologic model, used to constraint the grade interpolation for the reserve model, was used to constrain also the simulated models. Therefore, the conditional simulations described here do not take into account the uncertainty related to geologic interpretation and modeling.

The Original Block Model and Mine Plan.

The block model was built using 25x25x15m blocks, and applying the hard oxide and leached material boundaries interpreted by the mine geologists, processed into three-dimensional solids. The interpolation method was ordinary kriging, and used all the 15m drill hole bench composites available, in addition to the required correlogram models. In addition, other geologic units estimated in the model include Mixed, Secondary Enriched, and Primary material. The mine is for now only mining the oxide Cu portion of the deposit.

The block model was used to plan production at an accelerated rate, per the expansion program. The mine plan was based on unit production periods of one month for production year 1998, semi-annually for 1999, and yearly for production years 2000 through 2002 inclusive. Management decided to initially study the first five years of expanded production, though the simulations described here covered material to be produced up to year 2005.

The mine plan was developed by the local mine engineers, and resulted in mining limits for the periods described in the paragraph above. These same mining limits were used to “cut” the simulations produced, thereby obtaining a per period comparison between the predicted tons and grade above cutoff of the block model with respect to each of the simulations produced, as described below.

The process described amounts to quantify the risk (upside or downside) of ***minable reserves***, meaning the “received at mill”, or delivered grades and tons. These are the quantities that determine actual cash flows. Thus, the ***Transfer Function*** includes in this case all the steps performed to obtain a detailed mine plan, including pit optimization (based on the original block model) and a schedule based on appropriate production units.

The Conditional Simulations

The conditional simulations used in this study were developed using the Sequential Gaussian method (Isaaks, 1990). The grid chosen to develop the simulations was 5x5x15m, and there were 11 simulations generated in all. According to the technique involved, first the Cu variable is transformed into a Gaussian variable (Normal Scores transformation); the variogram of the transformed variable is modeled, as well as the correlogram of the original Cu variable. The simulation is performed on the transformed Gaussian variable, and then the output simulation is transformed back to the original space (%Cu). Several checks are performed to verify that the 11 output simulations reproduce correctly the original (Cu) histogram and correlogram. Although never perfect, for this particular deposit reproduction of the histogram and correlogram was achieved with relative ease.

In addition, separate grids were developed for the blocks classified as oxide and leached material, according to the solids representing the geologic model. A total of just under 7,400,000 nodes were simulated. The smaller grid is then averaged to the same block sizes as the block model used to develop the mine plan. Thus there are 25 simulated nodes within the 25x25x15m block. This averaging in fact models directly the volume-variance effect of the deposit, thus obtaining the predicted ***recoverable reserves***.

RESULTS

Two main results were derived from the 11 simulations:

- An F_1 grade factor was defined as:

  A second F1 factor was defined by changing the numerator in the equation above, and using the grade used in the mine plan (referred to as ‘Prog 1998'). This is in fact a factored grade, used by the mining engineer in developing the mine plan; it is based on the block model grade, to which the mine planner applies a heuristic conservative factor on a production unit basis. In both cases, a value greater than one implies that, according to the average of the 11 simulations, there is a downside risk (in percent as given by F_1) to the predicted grade of the block model or the planned grade. F_1 is calculated not only for the overall grade predicted by the model or the mine plan to be achieved for the five year period, but also for each production unit individually (monthly, semi-annually, or annually, depending on the year).
- Confidence limits for each production unit, and corresponding averages. Management decided to accept discarding the lowest and highest available simulation, and therefore the 9 remaining simulated values per block represent almost 82% confidence (9/11=0.818) that the true value is within the limits obtained. This of course assumes that the minimum and maximum simulated values obtained represent the absolute minimum and maximum that could be found for the model developed. As seen from the results presented, this is a reasonable assumption for this deposit.

Figure 2 shows the F_1 grade factors for monthly production as planned for 1998. Note how the factors vary significantly from month to month. The Mod 97 F_1 factor for the month of March is 1.124, that is, there is a 12% potential downside in grade when comparing the average of the simulation to the block model grade. Interestingly enough, the mine planner had cut that month's grade from the block model from 0.75 to 0.66% Cu; the conditional simulations in this case validate the heuristic planned grade.

Figure 3 shows the same factors results on a semi-annual basis, for 1998 (averaged from the monthly production units) and 1999. The impact of averaging is quite evident, as is the increasing risk for under-performance of both the Block Model grade and the corresponding Planned Grade. Figure 4 shows again the F_1 grade factors for a yearly production unit, from 1998 through 2002. The factors suggest that the block model overestimates grade for most of the years considered. Observe how the heuristic (planned) grade will perform significantly better in general, although for the latter years it still overestimates the predicted grade according to the conditional simulations.

Figures 5 through 7 show the same three production units (monthly for 1998, semi-annually for 1998 and 1999, and yearly for 1998 through 2002), this time graphing the upper and lower intervals obtained from the simulations, and the block model and planned grade averages. Recall that these intervals shown correspond to the range of possible values obtained by discarding the minimum and the maximum simulated value for each block.

Note in Figure 5 several interesting points. For example, the programmed grade for March 98 falls almost in the middle of the simulation confidence interval, while the block model grade falls outside the same interval. For the months of May and December, both estimates are too conservative, according to the simulations, while for the month of October the simulation model suggests that the planned grade will not be achieved. In general, confidence limits are not symmetric with respect to the estimated values, and these estimates may not even fall within the interval! This illustrates why it is preferable to obtain a model of uncertainty by dissociating the tasks of estimation and of modeling uncertainty. Even in the case of a seemingly Gaussian-behaved variable (such as Cu grades in a porphyry copper deposit), uncertainty models that result from conditional simulations and Transfer Functions are obviously non-Gaussian.

CONCLUSIONS

Conditional simulations are quickly becoming standard tools for analyzing uncertainty within the mining industry. Industrial-scale simulations are now fairly common, and recommended as standard tools for studying resource and reserve estimation related problems. In particular, they have demonstrated their usefulness when a model of uncertainty is required after applying transfer functions.

The case study has shown an example of processing and incorporating a more sophisticated risk analysis into a feasibility study through conditional simulations. In this particular case, the Operations Management team at the mine was interested in understanding the levels of risk involved in a given mine plan, which was used to predict cash flows from a proposed expansion.

The main conclusions from this work are:

· The benefits of detailed, geology-based risk analysis on the reserves and mine plan justify the additional effort of developing conditional simulations.

· Conditional simulations allow for unmatched flexibility in analyzing related problems, such as drill hole density, justification of in-fill drilling in areas of greater risk from the production standpoint, reserve classification, block model and recoverable reserves validation, etc.

· Conditional Simulations result in a rational description of uncertainty, providing geologic justification basis for the use of recovery and correction factors in mine planning.

· The planned expansion was approved based on the confidence limits described. Additionally, Management decided to plan detailed future in-fill drilling campaigns with the objective of reducing the risk for certain production units.

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